J Quant Criminol
DOI 10.1007/s10940-016-9313-x

ORIGINAL PAPER

# The Influence of Community Areas, Neighborhood Clusters, and Street Segments on the Spatial Variability of Violent Crime in Chicago

**Cory Schnell**[1] · **Anthony A. Braga**[2] · **Eric L. Piza**[3]



**Abstract**
*Objectives* The influence of three hierarchical units of analysis on the total spatial variability of violent crime incidents in Chicago is assessed. This analysis seeks to replicate a recent study that found street segments, rather than neighborhood units of analysis, accounted for the largest share of the total spatial variability of crime in The Hague, Netherlands (see Steenbeek and Weisburd J Quant Criminol. doi:10.1007/s10940-015-9276-3, 2015).
*Methods* We analyze violent crime incidents reported to the police between 2001 and 2014. 359,786 incidents were geocoded to 41,926 street segments nested within 342 neighborhood clusters, in turn nested within 76 community areas in Chicago. Linear mixed models with random slopes of time were estimated to observe the variance uniquely attributed to each unit of analysis.
*Results* Similar to Steenbeek and Weisburd, we find 56–65 % of the total variability in violent crime incidents can be attributed to street segments in Chicago. City-wide reductions in violence over the observation period coincide with increases in the spatial variability attributed to street segments and decreases in the variability attributed to both neighborhood units.
*Conclusions* Our results suggest that scholars interested in understanding the spatial variation of crime across urban landscapes should be focused on the small places that comprise larger geographic areas. The next wave of "neighborhood-effects" research should explore the role of hierarchical processes in understanding crime variation within larger areas.

✉ Cory Schnell
cory.schnell@rutgers.edu

[1] School of Criminal Justice, Rutgers University, 123 Washington Street, Newark, NJ 07102, USA

[2] School of Criminology and Criminal Justice, Northeastern University, Boston, MA, USA

[3] John Jay College of Criminal Justice, City University of New York, New York, NY, USA

Published online: 14 July 2016

**Keywords** Street Segment · Crime and place · Law of crime concentration · Chicago · Neighborhoods

## Introduction

Criminologists and urban sociologists have long been interested in explaining the spatial variation of crime within cities. One focus has been on understanding how community dynamics influence levels of crime and the development of criminal behavior within moderately-sized ("meso-level"), bounded geographic areas (see, e.g. Burgess 1925; Simcha-Fagan and Schwartz 1986; Sampson and Groves 1989; Sampson and Wilson 1995; Kirk and Papachristos 2011). This long-standing criminological tradition of studying crime at large within-city areas, such as communities and neighborhoods, has led to the development of core theoretical concepts such as social disorganization, informal social control, concentrated disadvantage, and, more recently, collective efficacy (Shaw and McKay 1942; Bursik and Grasmick 1993; Sampson et al. 1997). Indeed, in the landmark book *Great American City: Chicago and the Enduring Neighborhood Effect*, Sampson (2012, pp. 46) concludes that "a number of crime- and health-related problems come bundled together at the neighborhood level *and* are predicted by neighborhood characteristics such as concentration of poverty, racial isolation, single-parent families, and to a lesser extent rates of residential and housing instability."

Another focus has been on understanding the intra-city variation of crime at small ("micro") places such as specific addresses, intersection areas, and street segments (Weisburd et al. 2009). Seminal studies in Boston and Minneapolis revealed that only 5 % of the addresses in each city generated roughly 50 % of citizen emergency calls for service to the police (Pierce et al. 1988; Sherman et al. 1989). Even within high-crime neighborhoods, these studies suggested that crime clustered at a few discrete locations, leaving blocks of areas relatively crime-free. Recent longitudinal analyses have also found that the "criminal careers" of high-activity micro places within neighborhoods were relatively stable over long periods of time, suggesting the crime prevention programs should be focused on micro-geographic units (Weisburd et al. 2004; Braga et al. 2010, 2011). Reflecting on the larger body of empirical evidence and his own analyses of crime in five larger cities and three smaller cities, Weisburd (2015, pp. 133) suggests a "law of crime concentration" at places which posits, "that for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime."

The influence of various units of analyses has received much empirical attention in geographic criminology. Contemporary crime-and-place scholars have largely adopted a "small is better" approach, since micro-level units minimize within group heterogeneity (Oberwittler and Wikstrom 2009). Such spatial homogeneity helps to avoid the incorrect assumption that patterns observed across larger units apply equally to the mosaic of smaller units of which it is comprised (Johnson et al. 2009), a problem commonly referred to as the "ecological fallacy" (Robinson 1950). In this sense, many scholars have argued that using larger units of analyses, such as U.S. census tracts and block groups to represent neighborhoods and communities, masks important street-to-street

variations in crime within neighborhoods (Weisburd et al. 2012; Weisburd and Amram 2014; Andresen and Malleson 2011). In essence, these scholars suggest that much of the spatial variability in urban crime problems is being missed by empirical analyses focused on neighborhoods and communities (Eck and Eck 2012; Weisburd 2015). Other scholars have argued that micro units of analyses may not be appropriate in all contexts, with certain social processes and human behaviors occurring at a broader spatial scale (Boessen and Hipp 2015; Hunter 1985). In this sense, some have argued that both micro- and meso-units may be too narrow, suggesting macro-areas surrounding neighborhoods as an important scale of ecology in the study of crime (Hipp and Boessen 2015; Mears and Bhati 2006).

A recent analysis explored the relative importance of various geographic units of analyses by examining how much of the variability of crime in The Hague, The Netherlands could be attributed to micro (street segment), meso (neighborhood), and macro (district) levels of geography (Steenbeek and Weisburd 2015). While crime was concentrated in specific units at each level of geography, the study reported that between 58 and 69 % of the variability of crime was attributed to street segments, with most of the remaining variability occurring at the district level. Steenbeek and Weisburd (2015) concluded that social scientists' use of meso-geographic units missed most of the "action" in understanding crime variability and micro-geographic units were key to understanding urban crime problems.

In this study, we replicate the work of Steenbeek and Weisburd (2015) by analyzing the spatial variability of violent crime incident data at different levels of geography in Chicago, Illinois between 2001 and 2014. As will be described briefly below, Chicago is a particularly important setting for this line of academic inquiry as it is well-known for a series of seminal studies of neighborhood effects on a variety of human behaviors and outcomes (Burgess 1925; Shaw and McKay 1942; Sampson et al. 1997; Sampson 2012). Violent crime concentrations at community areas, neighborhood clusters, and street segments are described using Lorenz curves and Gini coefficients. To estimate the variance attributed to each geographic level, linear mixed models with random slopes of time are used. Similar to Steenbeek and Weisburd (2015), we find that violent crime in Chicago is most heavily concentrated on the street segment level while neighborhood clusters and community areas also experience similar levels of concentration. These findings provide further evidence that the variability of crime within cities is best captured at micro-units of analysis, such as street segments.

## The Relevance of Micro-Geographic Units of Analysis in Criminology

For most of the last century, criminologists have focused their understanding of the variability in the spatial distribution of crime on communities rather than the specific small places that comprise these larger geographic areas (Weisburd et al. 2009; Eck and Weisburd 1995). Criminologists have often tried to explain why certain types of crime or different levels of criminality are found in some communities as contrasted with others (e.g. see Agnew 1999; Bursik and Grasmick 1993; Sampson and Groves 1989; Shaw and McKay 1942) or how community-level variables, such as relative deprivation, low socioeconomic status, or lack of economic opportunity may affect individual criminality (e.g. see Agnew 1992; Cloward and Ohlin 1960; Merton 1938; Wolfgang and Ferracuti 1967). Recent research on neighborhood social mechanisms and processes suggests that

levels of "collective efficacy" (defined as social cohesion combined with shared expectations for social control) were strongly associated with variations in violent crime across neighborhoods (Sampson et al. 1997; Morenoff et al. 2001).

Urban sociologists suggest that neighborhoods can be thought of as ecological units nested within successively larger communities (Sampson et al. 2002); that is, a neighborhood is a collection of both people and institutions occupying a spatially-defined area influenced by ecological, cultural, and sometimes political forces (Park 1915; Suttles 1972). Most studies of neighborhoods rely on geographic boundaries defined by the U.S. Census Bureau or other administrative agencies (e.g. school districts, police districts). Although Census tracts and block groups are generally consistent with the conception of overlapping and nested ecological structures, administratively-defined units offer imperfect operational definitions of neighborhoods for research and policy (Sampson et al. 2002). In recent years, social scientists have become increasingly interested in defining neighborhoods that respect the logic of street patterns and the social networks of neighbor interactions (Grannis 1998).

Over the course of the 1990s and continuing into the 2000s, social science inquiries examining the influence of neighborhood effects on crime and other social outcomes increased dramatically (Sampson et al. 2002). Roughly at the same time as this resurgence in neighborhood effects research occurred, strong criminological interest in small micro-geographic units of analysis, such as street addresses, intersection areas, and street segments, also emerged (Eck and Weisburd 1995; Weisburd et al. 2009). A series of cross-sectional research studies demonstrated that crime is highly concentrated at a small number of specific hot spot locations within cities (Pierce et al. 1988; Sherman et al. 1989; Eck et al. 2000; Bowers 2014). Empirical research also yielded evidence of a high degree of stability of crime at small places over time (Spelman 1995; Taylor 1997), suggesting that crime is strongly coupled to particular locations within neighborhoods.

An influential analysis of crime trends at specific street segments in Seattle over a 14-year period suggested that places have stable concentrations of crime events over time (Weisburd et al. 2004). The study also found that a relatively small proportion of places could be grouped as having steeply rising or declining crime trends and this subgroup of places was primarily responsible for overall city crime trends. Weisburd et al. (2004) observed that city crime trends could be better understood as strong changes generated by a relatively small group of micro places over time rather than a general process evenly spread across the city landscape (also see Curman et al. 2015; Wheeler et al. 2015). Similar findings on the concentration and stability of crime at specific places over time have been reported for fatal and non-fatal shootings (Braga et al. 2010) and robberies (Braga et al. 2011) in Boston. A growing body of experimental evaluation research suggests that focusing police resources on specific crime hot spot areas can significantly reduce crime without simply displacing criminals to nearby areas (Braga et al. 2014). Indeed, even Professor Robert Sampson (2011, pp. 224), well-known for his landmark research on neighborhood effects, has acknowledged the potential power of hot spots policing strategies, suggesting that these approaches "can more efficiently stave off epidemics of crime and its spatial diffusion."

Reflecting on the existing empirical evidence on crime concentration at micro places, some scholars suggest that analyses conducted at neighborhood, community, and larger geographic units miss a bulk of the underlying spatial variation of crime across city landscapes (Rengert et al. 2000; Sherman et al. 1989; Groff et al. 2009). A series of studies suggest that much is lost when spatial analyses of crime are conducted at larger

area levels when compared to micro-geographic levels of analyses. For instance, in two distinct longitudinal analyses of crime in Seattle, Weisburd et al. (2012) and Groff et al. (2010) find that local influences produce strong variability of crime patterns at the street segment level over extended time periods. Johnson (2010) applied Lorenz curves to compare observed and expected concentrations of burglary at the street segment level with observed and expected concentrations of burglary at the census area level in the United Kingdom.

Johnson (2010, pp. 354) found that the degree of concentration was greater at the street segment level and concluded, “the explanation for the distribution of crime cannot be found entirely in theories which consider sociological processes that operate at the area level. Other factors, which include the configuration of the street network, are at play.” In Vancouver, British Columbia, Andresen and Malleson (2011) apply a spatial point pattern test to analyze the stability in the spatial distribution of crime over time at three levels of aggregation: census tracts, dissemination areas (census blocks), and street segments. While Andresen and Malleson (2011) do not report statistics for crime concentration at the larger units of analysis, they find that very small percentages of street segments account for half of varying types of crime. They also find more stable crime concentration patterns across time for street segments than for larger spatial levels and conclude that street segments are the ‘‘driving force behind broader neighborhood change’’ (Andresen and Malleson 2011, pp. 74).

Unfortunately, the studies briefly described above do not directly compare the relevance of micro versus larger geographic trends in a single analysis. A key methodological issue involves unit-independence problems introduced by standard definitions of larger geographic units that prevent a single analysis that simultaneously considers crime variation at multiple geographic levels. As described by Steenbeek and Weisburd (2015, pp. 5), “census area definitions are based on census blocks, which include the four block faces on a block unit. However, the street segment includes both block faces on two block units.” In other words, street segments do not cluster directly within census block groups or tracts, and this produces boundary overlap problems.

Steenbeek and Weisburd (2015) overcame the methodological limitations of previous studies by using a multilevel dataset in The Hague that allowed the application of statistical methods to decompose the total crime variance at street segment (micro), neighborhood (meso), and district (macro) levels of analysis without boundary overlap problems. Their hierarchical analysis revealed that “most of the action” in crime variation across The Hague was attributed to street segments rather than higher geographic units. Between 58 and 69 % of the variability in the city’s crime problem was explained at the street segment level. The bulk of the remaining variance was contributed by the district level of analysis rather than the neighborhood level of analysis. Steenbeek and Weisburd (2015) were hesitant to draw broad conclusions about the use of neighborhood units of analysis to understand within-city variations in the spatial distribution of crime. They strongly recommended replicating their analyses in US cities before drawing unambiguous conclusions as their results from The Hague could simply reflect the differing structures of American and European cities.

## Data and Methods

The historical development of place-based criminology has strong roots in Chicago. As described above, the so-called Chicago School generated seminal empirical and theoretical contributions to our understanding of the spatial distribution of crime at neighborhoods within cities (Shaw et al. 1929; Zorbaugh 1929; Shaw and McKay 1942). Chicago has long served as a laboratory for decades of scholarship on the influence of neighborhood effects on crime (Bursik and Webb 1982; Sampson and Raudenbush 1999; Kirk and Papachristos 2011). Indeed, the highly-influential Project on Human Development in Chicago Neighborhoods (PHDCN) spawned a cottage industry of research testing the influence of neighborhoods effects on crime and other social outcomes. At the same time, Chicago has also been the research site for a growing number of micro-level analyses that considered the influence of micro places on criminal behavior within neighborhoods (see Block and Block 1995; St. Jean 2007; Bernasco and Block 2011). The historical importance of Chicago-based research in criminological thought on the spatial variation of crime within cities makes it an ideal US location to replicate Steenbeek and Weisburd's (2015) analyses.

### Violent Crime Data

Chicago is the third-largest city in the United States with population estimates during our study time period ranging from approximately 2.9 million residents in 2001 to 2.7 million residents in 2014.[1] Given the prominence of violence as an outcome in neighborhood (Sampson et al. 1997; Morenoff et al. 2001) and micro-level analyses (St. Jean 2007; Bernasco and Block 2011) in Chicago, our study focused on violent crime rather than total crime as analyzed by Steenbeek and Weisburd (2015) in The Hague. Our study uses geocoded violent crime incident data reported by the Chicago Police Department (CPD) between 2001 and 2014. These data were collected through the City of Chicago data portal.[2] It is well known that police incident data, such as the Federal Bureau of Investigation's Uniform Crime Reports, have shortcomings. For instance, crime incident data are biased by the absence of crimes not reported by citizens to the police and by police decisions not to record all crimes reported by citizens (see Black 1970). Although incident reports have flaws, careful analyses of these data can yield useful insights on crime (Schneider and Wiersema 1990).

We were primarily interested in understanding how much of the total violent crime variability across Chicago could be attributed to each level of spatial aggregation rather than understanding the crime variability across crime types. Moreover, as suggested by Steenbeek and Weisburd (2015), analyzing a general violence measure is preferable as specific violent crimes can be rare events at micro-geographic units such as the street segments used in this analysis. Therefore, in our main analysis, we combined aggravated assault, robbery, and homicide incidents into an aggregate violent crime measure. In subsequent sensitivity analyses, however, we consider each of the three violent crime types separately.

Like many US cities, yearly city-wide counts of violent crime incidents in Chicago decreased dramatically over the course of the study time period (Fig. 1). Overall, Chicago experienced a 52.2 % reduction in violent crime incidents from a high of 44,001 violent

[1] U.S. Census Quickfacts; http://quickfacts.census.gov/qfd/states/17/1714000.html.

[2] Incident report data was accessed from the data portal in February 2015; https://data.cityofchicago.org/.

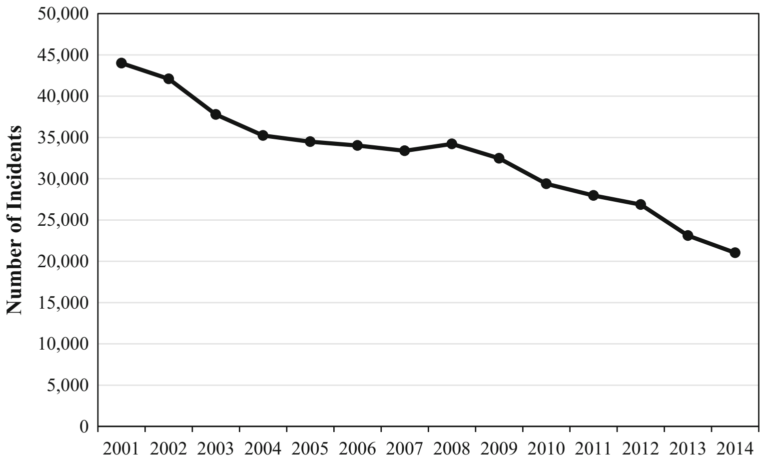



**Fig. 1** Violent crime incidents in Chicago, 2001–2014

events in 2001 to a low of 21,027 violent events in 2014. There was a steady violent crime decline between 2001 and 2007, with violence increasing briefly in 2008 only to decline sharply again between 2009 and 2014. Using ArcGIS 10.3 mapping software, we were able to geocode specific X–Y coordinates[3] for 99.3 % of the 456,060 total violent crime incidents[4] in Chicago across the entire study period.

## Units of Analysis

As described above, three levels of spatial aggregation were used in our analyses: community areas (macro), neighborhood clusters (meso), and street segments (micro). These levels of spatial aggregation were specifically selected because of their importance in understanding Chicago's geography and their previous use in social science inquiries (Sampson et al. 1997; Sampson 2012). Chicago is composed of 77 community areas and 343 "neighborhood clusters" defined by PHDCN.[5] Community areas were delineated in the 1920s by Chicago School researchers in conjunction with the city's Department of Public Health (Chicago Fact Book Consortium 1990). Driven by dissatisfaction with U.S. Census boundaries, these units were created to conform to preexisting natural and social boundaries observed in Chicago (Wirth and Bernert 1949; Hunter 1974). Community areas are widely recognized today by municipal administrative agencies, the media, and

[3] See "Appendix 1" for a discussion of the geocoding process.

[4] These 456,060 violent crime incidents represented only 8.0 % of the total crime incidents reported by the Chicago Police Department over our 14-year observation period. 51.6 % of the total violent crime incidents were aggravated assaults, 46.9 % were robberies, and only 1.5 % were homicides. Steenbeek and Weisburd identified 406,683 *total* crime incidents in The Hague from 2001 to 2009.

[5] Community area boundary files were accessed through the Chicago Data Portal. PHDCN data is publicly available but due to its confidentiality a data access proposal must be submitted to ICPSR. Proposals are submitted at: http://www.icpsr.umich.edu/icpsrweb/PHDCN/. Professor Robert Sampson generously provided the neighborhood cluster boundary files after our research team received approval from ICPSR (see Earls et al. 2007).

residents as the predominant neighborhood unit of analysis used to understand the geography of Chicago (Sampson 2012).

Neighborhood clusters are nested within Chicago's community areas; as such, both units of analysis often share common boundaries. Neighborhood clusters were created by the PHDCN research team (see Earls and Buka 1997; Earls et al. 2007; Sampson 2012) to explore heterogeneity within community areas without relying exclusively on census tracts which are frequently used as a proxy for neighborhoods (Bellair 2000; Sampson et al. 2002; Peterson and Krivo 2010). Two to three census tracts were combined based on PHDCN research team's knowledge of Chicago's local neighborhoods, major geographic boundaries, and cluster analyses of census data (Sampson 2012). The influence of PHDCN on contemporary neighborhood effects research has situated neighborhood clusters at the center of several promising advances in neighborhood based inquiry (see Sampson et al. 1997; Kirk and Papachristos 2011). Chicago has a total geographic expanse of nearly 230 square miles. However, the geographic sizes of community areas range from between 0.61 and 13.3 square miles (mean = 3.00 sq. miles), and the geographic sizes of neighborhood clusters range from as small as 0.08–10.52 sq. miles (mean = 0.67). Community areas averaged some 36,000 residents per area while neighborhood clusters averaged roughly 8000 residents per cluster.

Street segments, also referred to as street block faces, are an increasingly common unit of analysis used in place-based criminology (see Weisburd 2015) and are generally defined as "the two block faces on both sides of a street between two intersections" (Weisburd et al. 2004, pp. 290).[6] All crime incident report data in the Chicago Data Portal corresponds directly to an X–Y coordinate that was located on the actual street rather than the intersection of two or more streets. Therefore, unlike other micro-place analyses that developed "intersections" as a unit of analysis (e.g. Braga et al. 2010) or excluded crime incidents geocoded to intersections due to double-counting concerns (Weisburd et al. 2004), all violent crime incidents with X–Y coordinates were geocoded to street segments in this study.

There are 51,650 street segments in Chicago, with a mean length of 426.52 feet (SD = 233.49 feet) at the time our study was completed. Highways, interstates, and highway access points represented 2621 of these street segments and were excluded from the analysis.[7] There were also 703 street segments, one neighborhood cluster, and one community area excluded from our analysis after these places were identified as Chicago's O'Hare International Airport (see Sampson et al. 1999; Kirk and Papachristos 2011). 6400 street segments were excluded from the primary analysis because they either shared or

[6] A street map was obtained from Chicago's data portal and then was transformed to a street segment map using ArcGIS version 10.3. As noted in previous research (Weisburd et al. 2014) verifying the validity of spatial units raises some challenges. Specifically, GIS base maps (e.g. street networks) are typically drawn in a manner that reflects city zoning patterns and block level address ranges. This means that many street segments in a street network may not be "true street segments." In particular, certain street segments (the area between two intersections) may be represented by multiple lines. If left as is, the database would reflect multiple "street segments" where there was only truly a single street segment. To correct such errors, researchers visually reviewed each street unit within ArcGIS (using aerial imagery base maps) to ensure their accuracy, combining separate street segments into single units when necessary. Via this process, the original file of 55,747 street segments was converted to a final dataset comprising 51,650 street segments.

[7] Violent crime incidents occurring on these segments were rare and primarily recorded by the Illinois State Police, which patrols these locations instead of the CPD. As a result, almost all of these incidents did not appear in the Chicago data portal.

crossed a neighborhood cluster or community area boundary in Chicago.[8] After these exclusions, the final dataset included some 359,786 violent crime incidents distributed across 41,926 street segments nested within 342 neighborhood clusters nested within 76 community areas. Figure 2 illustrates the nested structure of these three units of analysis in Chicago.

## Analytic Approach

Following Steenbeek and Weisburd (2015), our analyses involved two stages. In the first stage, standard descriptive summary statistics were used to describe crime concentrations at the three levels of spatial aggregation. Lorenz curves were then applied to plot the cumulative percentage of spatial units against the cumulative percentage of crime for community areas, neighborhood clusters, and street segments (Lorenz 1905; see also Johnson 2010). The Gini coefficients of inequality were used to summarize the information presented in the Lorenz curves and discern trends in crime concentration distributions over time. Gini coefficients vary between 0 (suggesting an even distribution of crime across units) and 1 (suggesting a completely uneven distribution characterized by all crimes clustered in one unit), and represent the ratio of the area between the line of perfect equality and the observed Lorenz curve to the area between the line of perfect equality and the line of perfect inequality (Gastwirth 1972). In this analysis, the line of perfect equality would be represented as such: 1 % of street segments account for 1 % of violent crime incidents, 2 % for 2 %, and so on to 100 %.

The second stage of the analysis used linear mixed models (LMM, commonly known as hierarchical linear models) to quantify the amount of crime variation across the different units of analysis over time (see Raudenbush and Bryk 2002). Specifically, our panel data analyses involved estimating a four-level model of years nested in street segments nested in neighborhood clusters nested in community areas. A fixed effect of time was added to our longitudinal model to estimate the overall time trend (e.g. a decline in the number of crime events over the 14-year period). The slope of time was allowed to vary randomly across street segments (and/or neighborhood clusters and/or community areas) so different patterns of change over time per street segment (or neighborhood cluster or community area) could be captured.

Steenbeek and Weisburd (2015) estimated a LMM on a *sample* of street segments in The Hague. The authors conducted a bootstrapping procedure which drew 500 stratified random samples of 25 % of street segments per neighborhood; the authors' findings were based on averaged variance estimates across all of the replications. This procedure was used to satisfy an assumption of the random effects model that data assessed will be drawn from a random sample of a population for each level since the data represented the "population" of street segments in The Hague. For this analysis, estimates are reported from a single model for three key reasons. First, due to the exclusion of certain street segments (i.e. boundary overlap, highways) the remaining street segments represent a sample—albeit a non-random one—of the population of street segments in Chicago which partially satisfies the assumption.[9]

[8] 6117 street segments were excluded because they shared boundaries (95.6 % of 6400) and only 283 (4.4 %) were excluded because they crossed boundaries. These street segments were considered in sensitivity analyses to test the robustness of findings. Steenbeek and Weisburd (2015) divided the cross-neighborhood segments into two new segments. This analysis does not utilize this strategy because the number of these segments is negligible and this strategy would devalue the street segments as a stand-alone unit of analysis (i.e. favoring neighborhoods over segments).

[9] 51,650 street segments were initially identified before excluding 9724 thus creating a sample of 81.2 % of the original population. Even without this consideration, identifying the 51,650 street segments as a "population" is to some degree an arbitrary decision since these data could always be conceptualized to

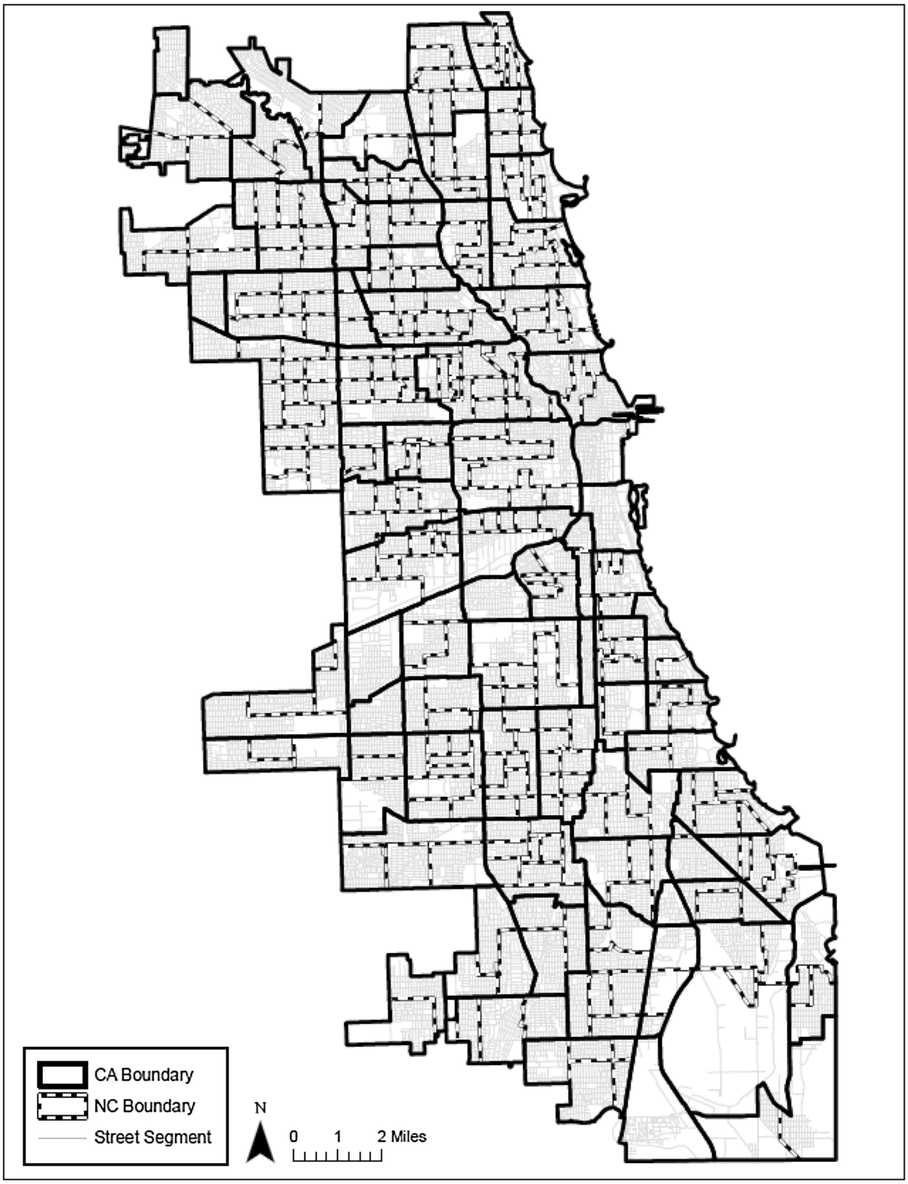



**Fig. 2** Spatial units used in the study; street segments nested within neighborhood clusters (NC) nested within community areas (CA) in Chicago

Second, Chicago is much larger than The Hague which creates a computational problem—which was already a concern for Steenbeek and Weisburd (2015). The Hague study assessed 9 years of total crime incidents geocoded to 15,527 street segments nested within 114 neighborhoods nested within 44 districts compared to our study which assesses 14 years of violent crime incidents geocoded to 41,926 street segments nested within 342 neighborhood clusters nested within 76 community areas in Chicago. The bootstrapping procedure was partially employed as a time efficient strategy to reduce the time of model estimation in The Hague research. However, this was no longer the case when the procedure was applied to Chicago.[10] Third, the other benefits of using the bootstrapping procedure described in Steenbeek and Weisburd (2015, pp. 8), such as addressing spatially correlated errors on the street segment level, could be recovered through conducting the procedure as a sensitivity analysis and comparing estimates to a single model which provides a more parsimonious analytic approach that includes all street segments.

Model estimation proceeded by first investigating whether an assumption of the linear model was violated by the distribution of the dependent variable residuals. Three-level hierarchical models (street segments nested in neighborhood clusters nested in community areas) were estimated using raw violent crime counts and logged violent crime counts[11] for each wave of data. Extreme violations of the normality assumption were detected in our reviews of residual diagnostic plots of the raw violent crime counts. However, diagnostic plots of the logged violent crime counts variable yielded only mild normality violations, suggesting it was more appropriate to use this dependent variable in our LMM (see Gelman and Hill 2007).[12] Restricted Likelihood Ratio Tests were used to determine whether the two-, three-, or four-level models best fit the panel data (see Rabe-Hesketh and Skrondal 2012). Our investigation revealed the best fit was obtained by the four-level model.

The logged street segment length was added as a covariate in our LMM since shorter street segments allow for fewer crime opportunities relative to longer street segments (see, e.g. Braga et al. 2010, 2011). Other covariates were not added as we were not interested in explaining crime variability by time-constant or time-varying predictor variables. Our investigation was simply interested in estimating the variability of crime across different

Footnote 9 continued

belong to a super-population (see Hartley and Sielken, 1975). In other words, the street segments in Chicago could be argued to be a sample of the street segments in Illinois or the violent crime incidents from 2001 to 2014 could be argued to be a sample of 14 years from the 179 years Chicago has been incorporated as a city.

[10] Indeed, the bootstrapping procedure on the Chicago data took approximately 3 days to return estimates from all 500 models. In comparison, a single model yielded estimates in approximately 1 h.

[11] This dependent variable was constructed by adding one to each observation and then taking the natural logarithm of the values: log (raw violent crime count + 1).

[12] Another approach would be to treat the dependent variable as count data and estimate generalized linear mixed models (GLMMs) that use a log link function and the probability mass function for the Poisson distribution. However, estimating a four-level GLMM model using the Chicago dataset presents a formidable computational challenge. Using Stata 14.1, for example, this model would not converge after running for three days. Additionally, as suggested by Steenbeek and Weisburd (2015), GLMMs are limited by a number of considerations for this kind of analysis that make interpretation of results much more complicated. For instance, while a simulation approach has been proposed as a solution (Browne et al. 2005), a disadvantage of GLMM is that the level-1 variance depends on the expected value and is therefore not reported by the Stata 14.1 software used in our analysis (and most other statistical packages). What is more, it was unlikely that our sampling distributions of the parameters were multivariate normal given the relatively small number of units per level in our models. This problem could be addressed by approximating the confidence intervals around our point estimates via parametric boot- strap methods (Efron, 1979). Fortunately, the log transformation of the violent crime measure yielded satisfactory residual diagnostics which allowed for the continued use of straightforward LMMs.

levels of geographic aggregation. While adding additional co-variates would likely influence the variance proportions, estimating an "empty" model provides an insightful baseline representation of these proportions. We were interested in analyzing the effect of a time trend and, similar to Steenbeek and Weisburd (2015), we found that a linear effect adequately captured the trends of crime over time. Divergent time effects for community areas, neighborhood clusters, and street segments were estimated by allowing coefficients of time to vary randomly at each spatial level. The final model has $t$ measurements nested within street segment $i$ nested in neighborhood cluster $j$ nested in community area $k$,

$$\begin{aligned} \log\left(Y_{tijk}+1\right) &= \beta_{0tijk} + \beta_{1ijk} time_{tijk} + \beta_2 \log(length)_{ijk} + \beta_3 \log(length)^2_{ijk} \\ \beta_{0tijk} &= \beta_0 + f_{0k} + v_{0jk} + u_{0ijk} + \varepsilon_{0tijk} \\ \beta_{1ijk} &= \beta_1 + f_{1k} + v_{1jk} + u_{1ijk} \end{aligned}$$

with correlated random effects, estimated using restricted maximum likelihood in Stata 14.1.

The variance of random effects was the primary focus of this study. The random slopes of time suggest these variances are not constant but depend on time. The estimated community area-level variance $\sigma^2_{f0}$, the neighborhood cluster-level variance $\sigma^2_{v0}$, and the street segment-level variance $\sigma^2_{u0}$ allow inferences of the crime variability, because they show the proportion of the total variance in crime that can be attributed to each spatial level.

## Results

Figure 3 presents the distribution of violent crime incidents across the three units of analysis between 2001 and 2014. The Fisher–Jenks algorithm is represented in the map's legend. This measure was used to classify each spatial level of analysis into five groupings such that the sum of squared deviations from the class means was minimized (Fisher 1958; Slocum et al. 2005). Across the 76 community areas in Chicago, Fig. 3 reveals that violent crime is concentrated in certain community areas on the west and south side of the city. These concentrations also appear to be relatively stable over the 14-year observation period

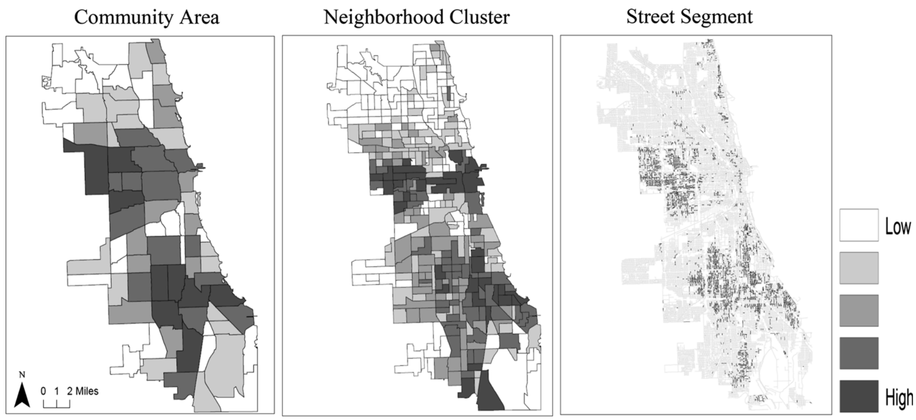



**Fig. 3** The spatial distribution of violent crime incidents in Chicago per unit of analysis, 2001–2014. *Note* Intervals based on Fisher–Jenks algorithm (see Slocum et al. 2005); community areas and neighborhood clusters were divided into groups of five but street segments were divided into two groups to improve the illustration of these units of analysis

(see "Appendix 2"). Compared to the community areas in Fig. 3, visualizing neighborhood clusters provides a more refined description of the spatial distribution of violence even within community areas with high levels of violent crimes. This spatial distribution of violent crime is also relatively stable over the observation period at neighborhood clusters in Chicago ("Appendix 3").

The transition from neighborhood clusters to street segments in Fig. 3 demonstrates the drastic magnitude increase in units of analysis (i.e. n = 342 to n = 41,926) which results in these units of analysis being more difficult to visualize. "Appendix 4" illustrates that, similar to community areas and neighborhood clusters, street segments experience relatively stable concentrations over the observation period. Figure 4 provides a closer inspection of the nested distribution of violent crime incidents in two community areas on the southside of Chicago with high levels of violence.[13] This figure begins to illustrate that violent crime in Chicago appears to follow descriptions of street-to-street variability of crime in other cities even within two of the most violent community areas (e.g. see Weisburd et al. 2012; Johnson 2010; Braga et al. 2010, 2011).[14] There is noticeable micro-geographic crime variation within these community areas; certain streets segments experience higher levels of crime over the 14-year period and other street segments experience much lower levels. Additionally, this figure demonstrates the importance of accounting for segment length in the LMMs because most of the segments in Group 2 are located running north-south and are visibility much longer then east-west segments.

Figure 4 also visualizes the between-street segments, within-neighborhood cluster, and within-neighborhood cluster-within-community area variability of violent crime events. Within neighborhood clusters (and community areas), all street segments are not created equal. Specific street segments experience much more violence than others. Coupled with the patterns observed in Fig. 3, these visualizations demonstrate that certain neighborhood clusters or community areas were generally safer than others. The remainder of our analyses quantifies this variation in local and larger area violent crime effects.

## Descriptive Statistics

To maintain parsimony in our presentation of analytic results, descriptive statistics on the percentage of spatial units that account for 50 % of violent crime are only presented for 2001, 2008, and 2014. Like Steenbeek and Weisburd (2015), a large share of crime was concentrated at a very small percentage of street segments in each wave of our panel data. Indeed, the spatial distribution of violent crime in Chicago followed Weisburd's (2015) law of crime concentration. As shown in column (a) of Table 1, 50 % of all violent crime incidents occurred in only 5.5–7.2 % of all street segments (roughly 2700 of the 41,926 segments). In contrast, about 21.1–24.0 % of neighborhoods clusters (72–82 of 342 neighborhood clusters) and 18.4–19.7 % of community areas (14–15 of 76 community areas) were responsible for 50 % of all violent crime incidents.

[13] See "Appendix 5" for an illustration of the nested distribution of violent crime incidents at these three levels of analysis in two community areas.

[14] Using the Fisher–Jenks algorithm to divide the distribution into two groups is by no means the most comprehensive strategy to summarize descriptive patterns of crime incidents over time at street segments (see Weisburd et al. 2004; Braga et al. 2010; Curman et al. 2015) but it does provide a preliminary tool to begin to illustrate differences in the spatial distribution of violent crime incidents. Coincidentally these two "low" and "high" groups represent an average of 0–1.9 incidents per year (i.e. 0–27 total incidents; Group 1) and an average 2+ incidents per year (i.e. 28–443 total incidents; Group 2) across the 14 year observation period.

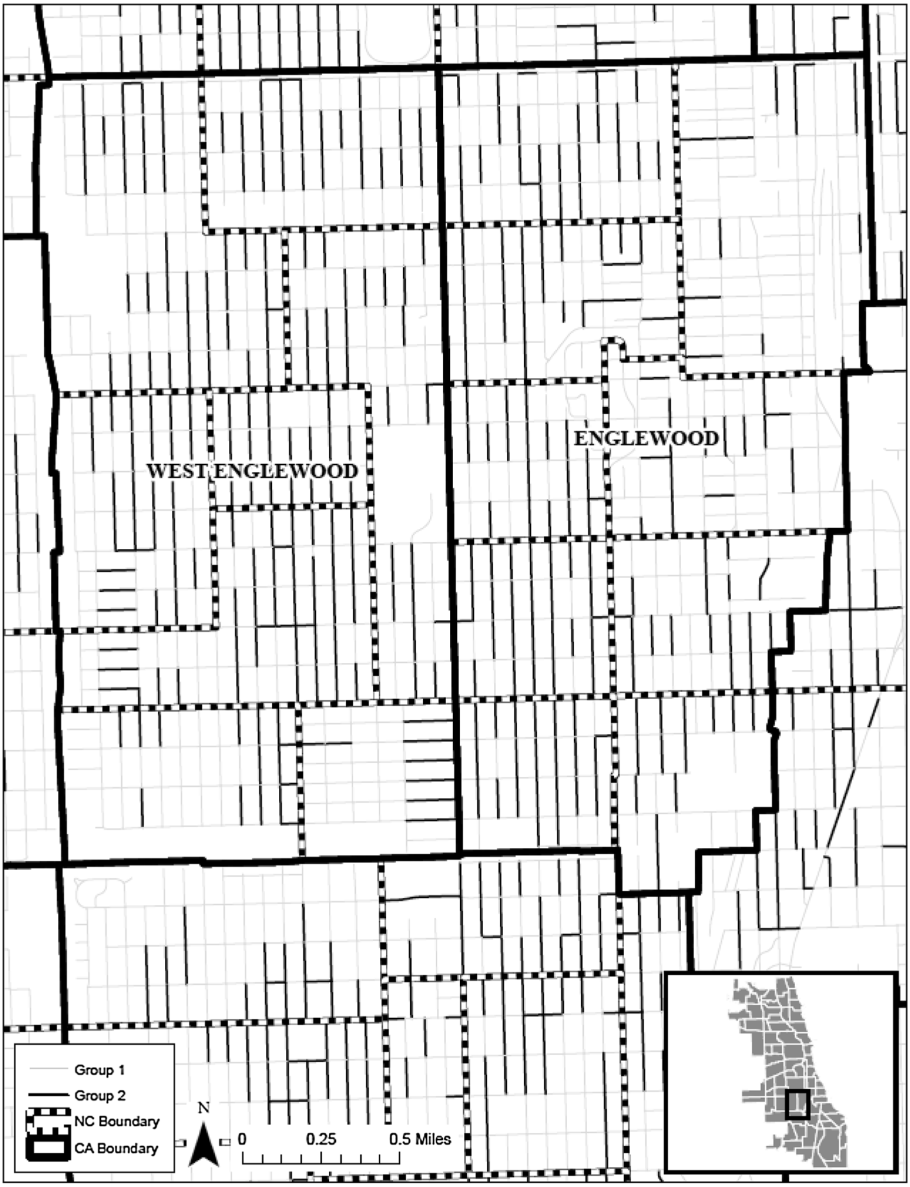



**Fig. 4** The distribution of violent crime incidents at street segments nested in neighborhood clusters nested within two community areas on the southside of Chicago, 2001–2014

**Table 1** Percent of spatial units accounting for 50 % of violent crime

| | (a) Percentage of spatial units accounting for 50 % of violent crime | | | (b) Percentage of spatial units that have any violent crime | | | (c) Percentage of spatial units with violent crime that account for 50 % of all violent crime | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2001 | 2008 | 2014 | 2001 | 2008 | 2014 | 2001 | 2008 | 2014 |
| Street segment | 7.2 | 6.1 | 5.5 | 34.8 | 29.0 | 22.1 | 20.7 | 20.9 | 24.7 |
| Neighborhood cluster | 23.1 | 24.0 | 21.1 | 100.0 | 100.0 | 99.7 | 23.1 | 24.0 | 21.1 |
| Community area | 19.7 | 18.4 | 18.4 | 100.0 | 100.0 | 100.0 | 19.7 | 18.4 | 18.4 |

N = 41,926 street segments, 342 neighborhood clusters, 76 community areas

Column (b) of Table 1 reports the percentage of spatial units that have at least one crime occurrence. Almost every neighborhood cluster and community area in Chicago experienced at least one violent crime per year during each year in the study time period. Alternatively, over two-thirds of Chicago street segments in each year between 2001 and 2014 did not experience a violent crime.[15] These results are very similar to findings of total crime incidents from The Hague (Steenbeek and Weisburd 2015) and Vancouver (Andresen and Malleson 2011). Finally, column (c) in Table 1 shows, of those non-zero spatial units, the percentage of units that accounts for 50 % of all crime. Since nearly all neighborhood clusters and all community areas experience at least one violent crime event in each wave of data, these percentages do not differ much from column (a). For street segments in 2001 (as one example), however, within the 7.2 % of street segments that experience at least one violent crime event (3019 street segments) about 20.7 % (625 segments) generate 50 % of all violent crime. This reveals that street segments have higher degrees of crime concentrations relative to neighborhood clusters and community areas when the focus is limited only to places that experience any violence.

Figure 5 presents the 2001–2014 violent crime concentration distribution for the three spatial units of analysis in Chicago.[16] This presentation of the points on the Lorenz curves allows the reader to make their own decisions on comparative cut-off points rather than arbitrary, pre-defined cut-off points (such as those used in Table 1). As shown in Fig. 5, violent crime was concentrated at every level of spatial concentration. However, street segments exhibit higher degrees of violent crime concentration relative to larger spatial units, namely neighborhood clusters and community areas.

As described above, Gini coefficients were used to summarize the degree of violent crime concentration in the Lorenz curves for each wave of data for the three spatial levels. As previously shown by Steenbeek and Weisburd (2015), the Gini coefficient is the ratio of the area that lies between the line of equality and the Lorenz curve over the total area under the line of equality.[17] Figure 6 confirms that crime is highly concentrated and moderately

[15] Over the entire study period 75.0 % of street segments experienced at least one violent crime incident.

[16] Lorenz curves for each individual year within the observation period offer similar results; street segments display a slight increase in degree of concentration compared to neighborhood clusters and community areas since neighborhood clusters and community already have practically 100 % of units having an incident (i.e. can't increase) while street segments only have room to increase over time.

[17] Figure 5. displays an inverted Lorenz curve that is best suited to visualize the spatial distribution of crime incidents while Gini coefficients are calculated on Lorenz curves facing the opposite direction. This does not influence the calculation of the Gini coefficient.

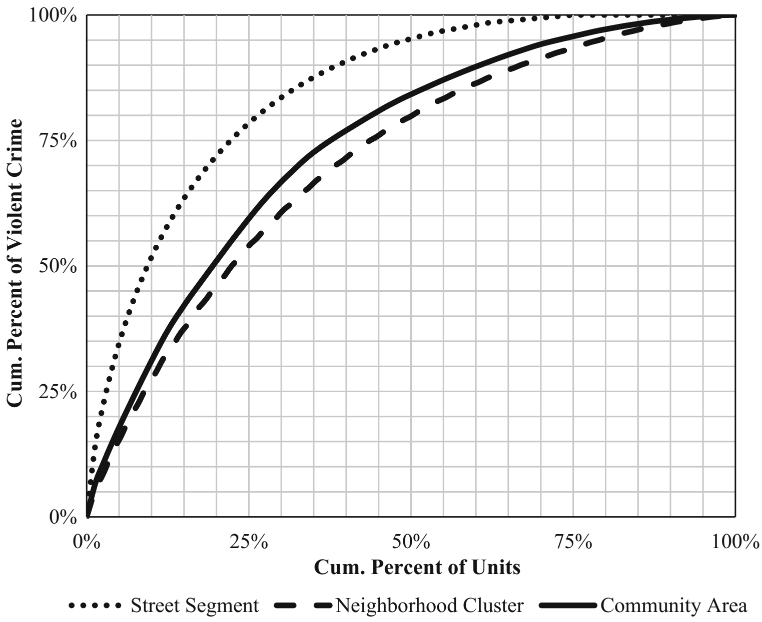



**Fig. 5** Lorenz curves for violent crime incidents in Chicago from 2001 to 2014

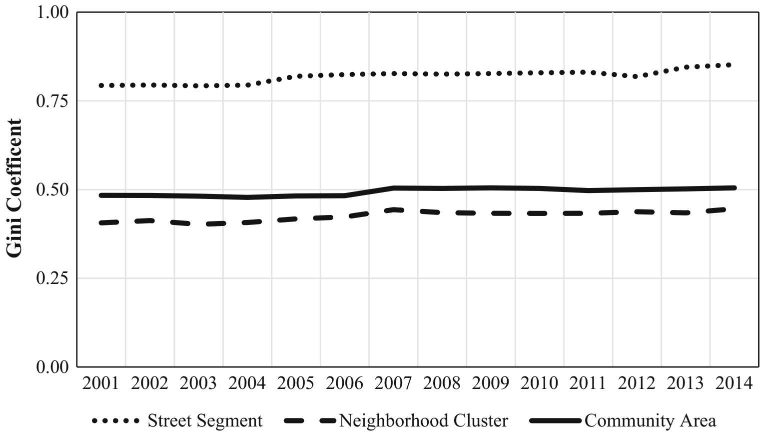



**Fig. 6** Gini coefficient for violent crime for all spatial units, 2001–2014

increasing over time for street segments with a Gini coefficient of .793 in 2001 which grows to .825 in 2008 and .852 in 2014. The concentration of crime for neighborhood clusters and community areas is still quite substantial (around the 0.4–0.5 mark on a scale of 0–1), although crime is certainly less concentrated on these higher levels of spatial aggregation. In addition, there is general stability in coefficients across both of these spatial units over the observation period. The Gini coefficient for neighborhood clusters starts at .406 in 2001 and finishes at .446 in 2014 while the coefficient for community areas starts at .484 in 2001 and finishes at .505 in 2014.

It is noteworthy that the degree of violent crime concentration at the neighborhood cluster level and the community area level is very similar. Indeed, as previously observed by Steenbeek and Weisburd (2015) in The Hague, this pattern could indicate that there is comparatively high within-community area (between-neighborhood cluster) homogeneity in violent crime concentration. This suggests that the neighborhood cluster level may not explain much about violent crime concentration beyond what was already observed at the higher community area level.

## Linear Mixed Models

Thus far, our descriptive analyses have shown that substantial violent crime variability exists at each level of geographic aggregation. However, these analyses disregard the nested structure of our geographic units of analysis and do not directly describe the proportion of violent crime concentration at each spatial level. LMMs allow a joint analysis of the amount of violent crime concentration at each level of spatial aggregation and for each data wave. Our LMM was designed to provide a direct estimate for the total share of violent crime at each level of geography over time.

Directly replicating the work of Steenbeek and Weisburd (2015), we estimated a four-level model of waves of data nested within street segments, nested within neighborhood clusters, nested within community areas. Inferences on violent crime variation for the three spatial levels can be made based on the proportion of the total variance in violence that is attributed to each geographic level. Since each spatial level allows the effect of time to vary randomly, the variance for each level depends on time. The street segment variance, for instance, is calculated by:

$$var\left(u_{0ijk} + u_{1ijk}time_{tijk}\right) = \sigma_{u0}^2 + 2\sigma_{u01}time_{tijk} + \sigma_{u1}^2 time_{tijk}^2$$

with $\sigma_{u01}$ referring to the covariance between the random effect of street segment and the random slope of time. Equivalent calculations are used to estimate the variance functions for community areas and neighborhood clusters.

The variance functions for the community area, neighborhood cluster, and street segment levels as a function of time are presented in Fig. 7.[18] The variance in violent crime that can be attributed to the community area and neighborhood cluster levels of analysis does not exhibit substantive nonlinearity and is consistently very small over time. The variance of violent crime at both levels *decreases* over the 14-year period, indicating increasing within-neighborhood cluster and within-community area variability in violent crime over time. In contrast, most of the variation in violent crime occurs at the street segment level. Our LMM demonstrates a non-linear change in violence variance at the street segment level over time that decreases significantly and then flattens.

Figure 8 presents the proportion of total variance attributed to the community area, neighborhood cluster, and street segment spatial levels for each wave of data during the 14-year observation time period.[19] The reported proportions represent the proportion of variance in violent crime of each spatial unit as compared to the total variance in violent

[18] The level-1 residual variance for these LMMs captures the "variance of time that can be attributed to time-varying explanations" (Steenbeek and Weisburd, 2015, pp. 14). This estimate from the final model was observed to be .120.

[19] The point estimate for each variance component was used to calculate the proportions shown in Fig. 7. As each variance represents an estimated parameter in the LMM, there is a 95 % probability that the ±1.96 SD confidence interval around this point estimate captures the true population mean.

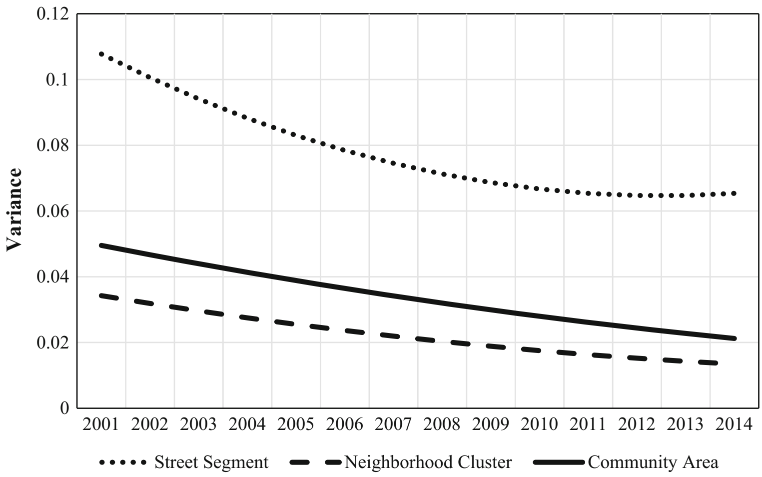



**Fig. 7** Variance functions per spatial level, 2001–2014

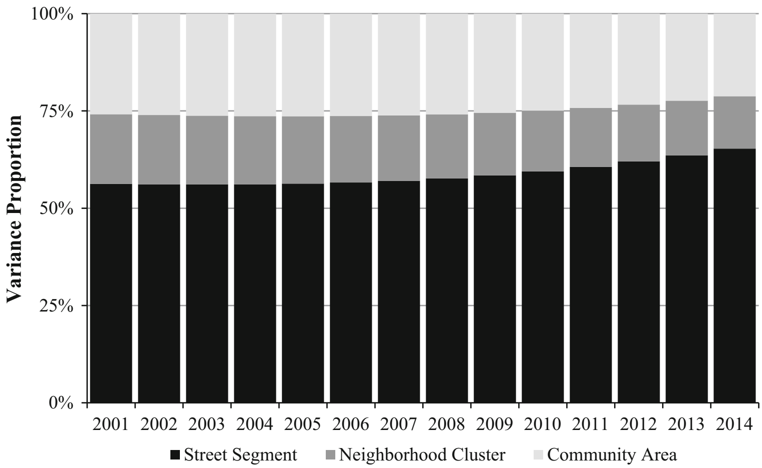



**Fig. 8** The proportion of total variance attributed to spatial levels, 2001–2014

crime attributed to the three spatial units (net the level-1 residual variance of crime). On average, about 58.7 % of the total variance can be attributed to variation between street segments across the years. Community areas account for about 25.1 % on average, while between-neighborhood cluster variance (controlled for street segment and community area level variability) accounts for about 16.2 % of the total variance on average. The results also demonstrate an increasing degree of crime concentration at the street segment level over time: from 56.3 % in 2001 to 65.3 % in 2014. The proportion of total variance accounted for by the neighborhood cluster-level decreases between from 17.9 to 13.4 % while the community area-level variance proportion decreases from 25.9 % in 2001 to 21.2 % in 2014.

The LMM estimates support the results of our descriptive statistical analyses in demonstrating that the bulk of violence is concentrated at the street segment level. The

neighborhood clusters and community areas generate similar but much smaller levels of crime concentration relative to street segments. Confirming the original work of Steenbeek and Weisburd (2015), these findings suggest that some community areas as a whole are more crime-prone than others, but that neighborhoods clusters within the same community area are rather homogeneous with regard to crime (either high or low). Nevertheless, most of the variability in violence occurs on street segments and the proportion of variability in violence attributed to street segments increases over time.

## Sensitivity Analyses

Sensitivity analyses were conducted to test the robustness of outcomes presented in this study. As described earlier, there were some methodological and analytical differences between our study and the work done by Steenbeek and Weisburd (2015). We explore how these differences may have impacted outcomes here. The first assessment applied the bootstrapping procedure conducted in The Hague study to test the robustness of our estimates. We followed the same parameters when conducting the stratified resampling of street segments in Chicago: 25 % of segments (n = 10,523) were randomly selected from within all 342 neighborhood clusters—which in turn represent all 76 community areas. Two sets of LMM estimates were observed, averaged variance components across 250 and 500 replications. Results for both sets were almost identical to the findings from the main analysis presented above. Street segments accounted for 57–65 % of the total variance proportion with neighborhood clusters and community areas accounting for 13–18 and 21–26 % respectively. Over time the variance proportion increased for street segments and decreased for the two neighborhood units of analysis as the number of violent crime incidents decreased in Chicago.

The second assessment included the street segments which were previously excluded because they were spatially located on the boundary of two or more neighborhood clusters or community areas. These 6400 street segments were randomly assigned to one of the various neighborhood clusters and/or community areas in which they were located. Once again, results were almost identical to findings from our main analysis. Street segments accounted for 56–66 % of the variance proportion while neighborhood clusters accounted for 13–19 % and community areas 21–25 %. The variance proportion for street segments also increased over time while the proportion decreased over time for neighborhood clusters and community areas. The third assessment, also conducted in the Steenbeek and Weisburd sensitivity analysis, removed outliers from our models. Approximately 1 % of street segments (N = 365) with the highest number of total violence incidents over the observation period were removed. Results for the variance proportion for each spatial level and their temporal trend were congruent with the main and sensitivity analyses presented thus far (street segments 55–65 %, neighborhood clusters 14–19 %, and community areas 22–27 %).

The fourth assessment disaggregated our general violent crime dependent variable into two specific categories of violence. These analyses revealed a modest increase in the importance of street segments relative to neighborhood clusters and community areas in decomposing the total variance proportion per spatial level in Chicago. For robbery incidents, street segments accounted for 63–69 % of the total variance proportion while neighborhood clusters explained 14–16 % and community areas explained 18–21 %. Since there were not enough homicide incidents to support an individual model, we combined homicides with aggravated assaults in an “assaultive violence” measure. For assaultive violence, 59–68, 13–17, and 19–23 % of the total variance proportion was accounted for by street segments, neighborhood clusters, and community areas respectively. For both

disaggregated violent crime outcomes, the variance proportion increased over time for street segments and decreased for neighborhood clusters and community areas. These findings are also very similar to those of Steenbeek and Weisburd (2015) which observed an increased proportion of the crime variance explained by street segments when they examined disaggregated crime trends.

The fifth assessment included property crimes in the dependent variable. With the inclusion of an additional N = 3,920,467 incidents over the study time period, the residual diagnostics for this LMM did not violate the normality assumption for the distribution of residuals. These analyses suggest an increased influence of street segments in comparison to neighborhood clusters and community areas in decomposing the total variance proportion per spatial level. Some 63–73, 11–16, and 16–21 % of the total variance proportion was attributed to street segments, neighborhood clusters, and community areas respectively with the variance proportion increasing over time for street segments and decreasing for the other two units of analysis. Overall, these sensitivity analyses confirm the estimates generated by our main LMM models are robust to varying methodological and analytical specifications.

## Conclusion

The results presented here are very supportive of Weisburd's (2015) law of crime concentration at places. In our longitudinal analyses of violent crime incidents in Chicago, we find that street segments accounted for some 59 % of the total variance, community areas accounted for about 25 % of the total variance, and neighborhood clusters only accounted for 16 % of the total variance in the spatial distribution of violence at each level of analysis over the course of a 14-year time period. What is more, our results also suggest an increasing degree of violent crime concentration at the street segment level over time. Indeed, our replication of Steenbeek and Weisburd's (2015:1) research in the Hague suggests that street segments are "where the action is in crime" while meso-sized neighborhoods clusters do not add much in understanding the spatial variability in violence beyond what larger community areas account for in Chicago. Similar to many descriptive empirical analyses, this study has limitations, such as the use of official police data that may not represent underlying levels of violence. Neighborhoods continue to be contextualized in new ways, such as recognizing the influence of social networks within and across communities on social outcomes, and future analyses may reconsider our representations of larger units of analysis (Sampson 2012; Hipp and Boessen 2015). Nevertheless, our findings are robust to a variety of supplemental model specifications and methodological approaches.

These findings do not suggest that community structures are not important to understanding spatial variation in crime across cities. More than a quarter of the spatial variation in violence was accounted for by variation at the larger community area level in Chicago. These results are generally supportive of the Chicago School's early observations on the salience of social processes and dynamics at play in broad areas of the city (see, e.g. Park 1915). The concentric zone model of the distribution of social problems and crime in Chicago included five large zones that extended from the city's business center (the "Loop") through to the more suburban areas of the city (Burgess 1925). Our analyses suggest that, to the degree that larger community areas in modern Chicago overlap with Burgess' (1925) conceptions of a series of communities with common characteristics, studying community structures and dynamics does add value to our understanding of spatial variation in crime across cities (also, see Steenbeek and Weisburd 2015 for a similar

observation). Perhaps these larger units are better positioned to capture community structures relative to medium-sized units such as neighborhood clusters. Further research is clearly necessary here.

Explaining the variation of crime within cities has been an enduring area of scientific inquiry in criminology. Social disorganization theory suggests that variations in crime within cities are impacted by community-level structural factors, such as relative deprivation, low socioeconomic status, or lack of economic opportunity, and mediated in important ways by informal social controls (Sampson and Groves 1989). The power of street segments in accounting for the spatial variation in crime in Chicago relative to community areas and neighborhood clusters suggests that criminologists need to pursue multi-level analyses to develop a more complete understanding of the social ecology of crime at places within cities (see Brantingham and Brantingham 1993; Deryol et al. 2016). Opportunity theories of crime, such as routine activity (Cohen and Felson 1979), rational choice (Cornish and Clarke 1986), and crime pattern theory (Brantingham and Brantingham 1981), have often been used to understand the place characteristics, situations, and dynamics that cause criminal events to concentrate at particular places. Community structures give rise to criminal opportunities at specific places within particular communities (Clarke 1995) suggesting an inherently multi-level theoretical structure to place-based criminology (see Taylor 2015; Wilcox and Land 2015).

The next generation of empirical inquiry on the spatial variability of crime within cities should seek to differentiate between theoretical processes operating at different geographic levels. A central point made by "neighborhood effects" research is that geographic social aggregations have meaning—there are processes, structures, institutions, cultures, and networks that powerfully shape social outcomes in larger areas. Institutions, for example, can be physically located on a single street segment but their influence on social outcomes can extend to much larger geographic areas. Hunter (1985) suggested three levels of informal social control within neighborhoods. The private level of control was grounded in intimate primary groups such as family and friends; the parochial level referred to relationships among neighbor and was rooted in broader local networks and institutions such as businesses, schools and churches; the public level focused on the ability of the community to secure goods and services from sources outside the neighborhood such as city and police departments. Hunter (1985) argued that effective control in neighborhoods requires agents at all three levels to work together. Inadequate social control at any level could influence criminal behavior at specific places within neighborhoods.

We believe that the Chicago and The Hague findings suggest that further empirical tests should be pursued to understand the criminological theories that could explain crime variation at each level of analysis and provide further guidance on how varying theories could be integrated given the multi-level nature of crime concentration patterns. Some scholars have suggested that social disorganization and routine activity theories are complementary and should be integrated (Miethe and Meier 1994). Indeed, both theories partially overlap in their treatment of social control as a key element in crime occurrences. In addition, Rice and Smith (2002) show how combining routine activity and social disorganization theories greatly improves the predictive power of spatial analyses to explain variations in auto theft incidents at block faces in a mid-sized southeastern U.S. city. In their examination of crime at street segments over a 16-year period in Seattle, Weisburd et al. (2012) build upon these studies not only to refine and strengthen the previous observations, but to propose an explanation for the observed crime concentrations, which integrates concepts from social disorganization and opportunity theories of crime. By comparing persistently hot street segments with very low/no crime street segments, they

found that variables supporting both opportunity and social disorganization theories of crime were associated with chronic high crime streets.

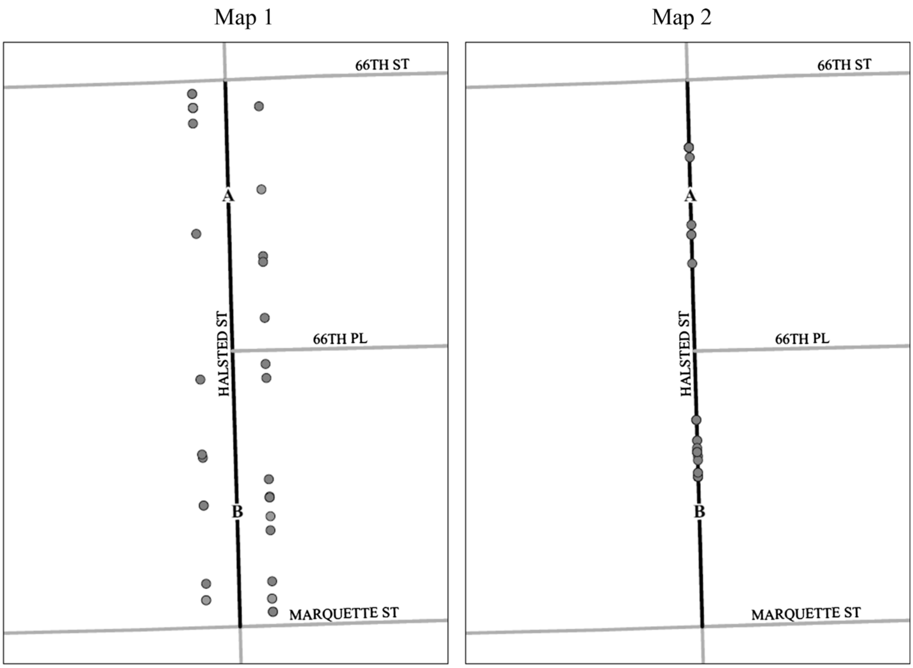
However, the proper domain to apply key theoretical concepts to understand variation of crime across and within neighborhoods still needs to be unraveled through ongoing empirical research. For instance, Weisburd et al. (2012) suggest that the level of "collective efficacy" on a street segment was associated with the amount of crime that occurs on that street segment. Braga and Clarke (2014) recently questioned whether the community-level concept of collective efficacy could adequately explain why a particular crime spot is persistently hot over time. They suggested that opportunity theory concepts such as guardianship best characterized levels of informal social control at street segments. Sampson (2013) also cautioned that smaller units, such as hot spots, are not necessarily better than larger units in understanding neighborhood social processes and figuring out how to mobilize collective efficacy. Sampson (2013) observes that micro places and conventional neighborhoods are nested within larger communities that are recognized or named by residents, external housing buyers, institutional actors such as real estate agents, and administrative agencies such as the police. Whether collective efficacy is best understood at the community level, street segment level, or both remains an open empirical question. Nevertheless, it is time for criminologists to begin developing some much needed new knowledge on how different theoretical perspectives may or may not fit across different levels of analysis in place-based crime research.

Thomas Kuhn (1962) noted that the potential for shifting paradigms in science rested, in part, on the ability of a specific scientific sub-community to gather human resources to act as a vanguard for a new way of thinking or doing science. Revolutionary ideas and new theoretical perspectives cannot move forward if converts are not drawn to the cause. As suggested by Laub (2004), the "life course" of criminology can be characterized by specific turning points that change how the field understands and responds to crime. Weisburd (2015) argues that it is time for another turning point in criminology and points to a relatively small but growing sub-community of scholars researching the criminology of place as showing great promise for advancing criminology as a science and improving its relevance for policy. We believe that the research presented here, highlighting the importance of micro places in understanding crime variation across Chicago—the mecca of neighborhood effects research, strongly supports his call for more scholars, old and young, to study the criminology of place.

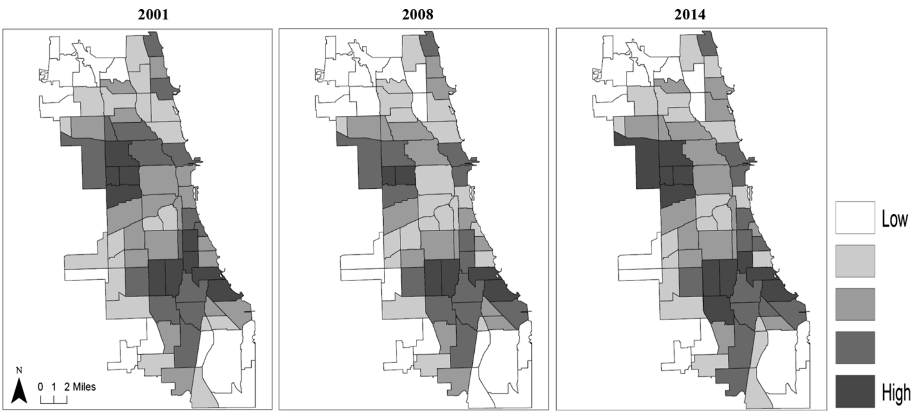
## Appendix 1: Geocoding Violent Crime Incidents in Chicago

Incident reports in Chicago's data portal are not attributed to specific addresses but are listed to 100 blocks of addresses. For example, all incidents occurring on the 6600 address block of Halsted Street are recorded as "66XX Halstead Street" in the data portal. While the incident locations are aggregated to the 100 block, the geographic X–Y coordinates for each incident correspond to a specific address, not a shared center point in the 100 block. Map 1 displays the 38 incidents recorded as "66XX Halstead Street" from 2012 to 2014. As illustrated, points fall at unique X–Y coordinates across street segments A and B within the 100 block. It should be noted that the process by which X–Y coordinates are recorded in Chicago's data portal has been recently modified. Map 2 displays the identical incidents in Map 1 but with new X–Y coordinates that center the incidents on the corresponding *street segment* within each 100 block. As can be seen, these points are geocoded to several locations at the center of the street

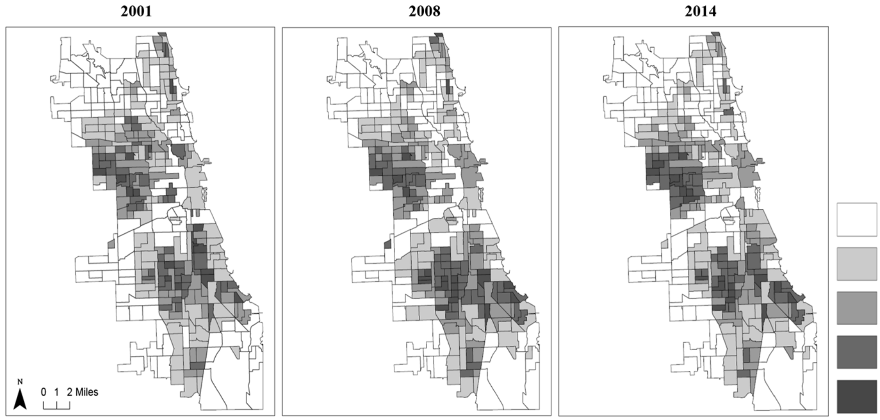
segments, rather than the precise street address. Incident reports for Map 1 were accessed in February 2015 while incidents for Map 2 were in May 2016. All incident reports assessed in this study were geocoded using the X–Y coordinates from Map 1 although for the purpose of this analysis both techniques would be appropriate.



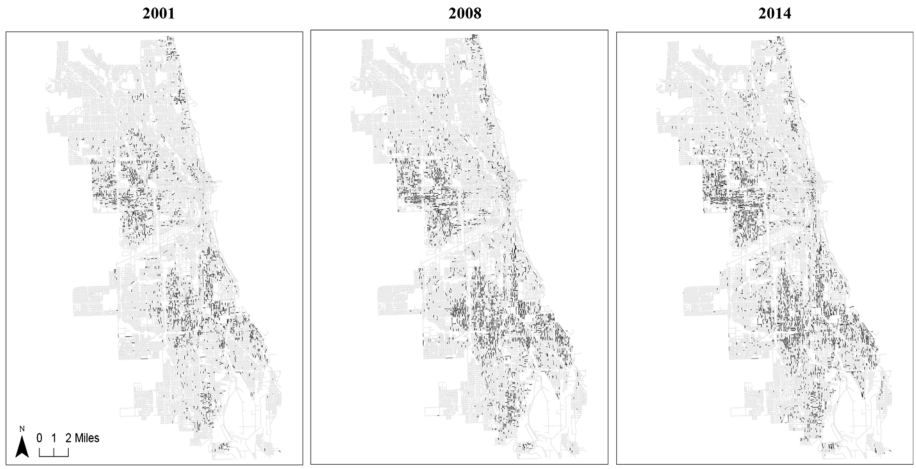

## Appendix 2: Violent Crime Rates (count per sq. mile) in Chicago per Community Area (2001, 2008, 2014)



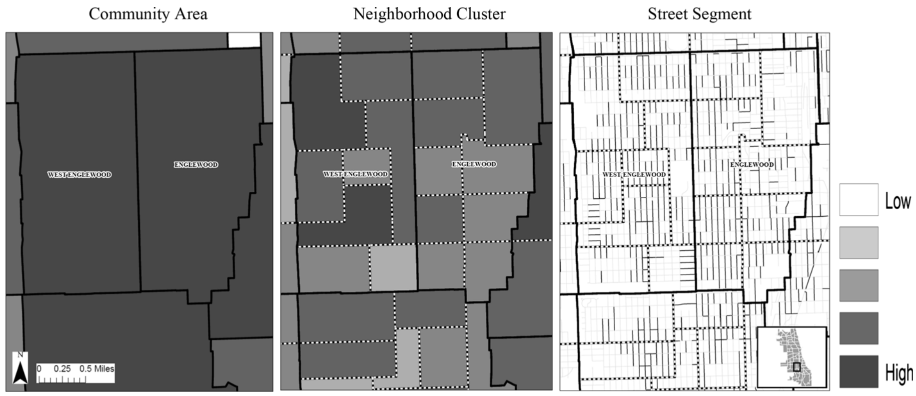
## Appendix 3: Violent Crime Rates (count per sq. mile) in Chicago per Neighborhood Cluster (2001, 2008, 2014)




## Appendix 4: The Spatial Distribution of Violent Crime Incidents at Street Segments in Chicago (2001, 2008, 2014)



## Appendix 5: Variability of the Distribution of Violent Crime Incidents per Unit of Analysis in Two Community Areas in the Southside of Chicago, 2001-2014




## References

Agnew R (1992) Foundation for a general strain theory of crime and delinquency. Criminology 30:47–87
Agnew R (1999) A general strain theory of community differences in crime rates. J Res Crime Delinq 36:123–155
Andresen MA, Malleson N (2011) Testing the stability of crime patterns: implications for theory and policy. J Res Crime Delinq 48:58–82
Bellair PE (2000) Informal surveillance and street crime: a complex relationship. Criminology 38:137–170
Bernasco W, Block R (2011) Robberies in Chicago: a block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. J Res Crime Delinq 48:33–57
Black D (1970) The production of crime rates. Am Soc Rev 35:733–748
Block LR, Block CB (1995) Space, place, and crime: Hot spot areas and hot places of liquor-related crime. In: Eck J, Weisburd D (eds) Crime and place: crime prevention studies, vol 4. Criminal Justice Press, Monsey, pp 145–183
Boessen A, Hipp J (2015) Close-ups and the scale of ecology: land uses and the geography of social context and crime. Criminology 53:399–426
Bowers K (2014) Risky facilities: crime radiators or crime absorbers? A comparison of internal and external levels of theft. J Quant Criminol 30:389–414
Braga AA, Clarke RV (2014) Explaining high-risk concentrations of crime in the city: social disorganization, crime opportunities, and important next steps. J Res Crime Delinq 51:480–498
Braga AA, Papachristos AV, Hureau DM (2010) The concentration and stability of gun violence at micro places in Boston, 1980–2008. J Quant Criminol 26:33–53
Braga AA, Hureau DM, Papachristos AV (2011) The relevance of micro places to citywide robbery trends: a longitudinal analysis of robbery incidents at street corners and block faces in Boston. J Res Crime Delinq 48:7–32
Braga AA, Papachristos AV, Hureau DM (2014) The effects of hot spots policing on crime: an updated systematic review and meta-analysis. Justice Q 31:633–663
Brantingham PJ, Brantingham PL (1981) Environmental criminology. Sage Publications, Thousand Oaks
Brantingham PJ, Brantingham PL (1993) Environment, routine and situation: toward a pattern theory of crime. In: Clarke R, Felson M (eds) Routine activity and rational choice. Transaction, New Brunswick, pp 259–294

Browne WJ, Subramanian SV, Jones K, Goldstein H (2005) Variance partitioning in multilevel logistic models that exhibit overdispersion. J R Stat Soc 168:599–613
Burgess EW (1925) The growth of the city: an introduction to a research project. In: Park RE, Burgess EW (eds) The city: suggestions for the investigation of human behavior in the urban environment. The University of Chicago Press, Chicago, pp 47–62
Bursik RJ, Grasmick HG (1993) Neighborhoods and crime: the dimensions of effective community control. Lexington Books, Lanham
Bursik RJ, Webb J (1982) Community change and patterns of delinquency. Am J Soc 88:24–42
Chicago Fact Book Consortium (1990) Local community fact book: Chicago metropolitan area. Academy Chicago Publishers, Chicago
Clarke RV (1995) Situational crime prevention. In: Tonry M, Farrington D (eds) Building a safer society: strategic approaches to crime prevention. The University of Chicago Press, Chicago
Cloward RA, Ohlin LE (1960) Delinquency and opportunity: a study of delinquent gangs. The Free Press, Glencoe
Cohen LE, Felson M (1979) Social change and crime rate trends: a routine activity approach. Am Soc Rev 44:588–605
Cornish DB, Clarke RV (1986) The reasoning criminal. Springer, New York
Curman ASN, Andresen MA, Brantingham PJ (2015) Crime and place: a longitudinal examination of street segment patterns in Vancouver, BC. J Quant Criminol 31:127–147
Deryol R, Wilcox P, Logan M, Wooldredge J (2016) Crime places in context: an illustration of the multi-level nature of hot spot development. J Quant Criminol. doi:10.1007/s10940-015-9278-1
Earls F, Buka SL (1997) Project on human development in Chicago neighborhoods. National Institute of Justice, Washington, DC
Earls FJ, Brooks-Gunn J, Raudenbush SW, Sampson RJ (2007) Project on human development in chicago neighborhoods: community survey, 1994–1995. ICPSR02766-v3. Inter-university consortium for political and social research [distributor], Ann Arbor. 2007-10-29. 10.3886/ICPSR02766.v3
Eck JE, Eck EB (2012) Crime place and pollution: expanding crime reduction options through a regulatory approach. Criminol Public Policy 11:281–316
Eck JE, Weisburd D (1995) Crime places in crime theory. In: Eck J, Weisburd D (eds) Crime and place: crime prevention studies, vol 4. Criminal Justice Press, Monsey, pp 1–34
Eck JE, Gersh JS, Taylor C (2000) Finding crime hot spots through repeat address mapping. In: Goldsmith V, McGuire PG, Mollenkopf JH, Ross TA (eds) Analyzing crime patterns: frontiers of practice. Sage Publications, Thousand Oaks, pp 49–64
Efron B (1979) Bootstrap methods: another look at the jackknife. Anna Stat 7:1–26
Fisher WD (1958) On grouping for maximum homogeneity. J Am Stat Assoc 53:789–798
Gastwirth JL (1972) The estimation of the Lorenz curve and Gini index. Rev Econ Stat 54:306–316
Gelman A, Hill J (2007) Data analysis using regression and multilevel/hierarchical models. Cambridge University Press, New York
Grannis R (1998) The importance of trivial streets: residential streets and residential segregation. Am J Soc 103:1530–1564
Groff E, Weisburd D, Morris NA (2009) Where the action is at places: examining spatio-temporal patterns of juvenile crime at places using trajectory analysis and GIS. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in geographic criminology. Springer, NewYork, pp 61–86
Groff ER, Weisburd D, Yang SM (2010) Is it important to examine crime trends at a local "micro" level?: a longitudinal analysis of street to street variability in crime trajectories. J Quant Criminol 26:7–32
Hartley HO, Sielken RL (1975) A "super-population viewpoint" for finite population sampling. Biometrics 31:411–422
Hipp J, Boessen A (2015) Neighborhoods, networks, and crime. In: Cullen F, Wilcox P, Sampson R, Dooley B (eds) Challenging criminological theory: the legacy of Ruth Kornhauser. Transaction, New Brunswick, pp 275–300
Hunter A (1974) Symbolic communities: the persistence and change of Chicago's local communities. The University of Chicago Press, Chicago
Hunter A (1985) Private, parochial, and public social orders: the problem of crime and incivility in urban communities. In: Suttles G, Zald M (eds) The challenge of social control: citizenship and institution building in modern society. Ablex, Norwood, pp 230–242
Johnson SD (2010) A brief history of the analysis of crime concentration. Eur J Appl Math 21:349–370
Johnson S, Bowers K, Birks D, Pease K (2009) Predictive mapping of crime by ProMap: accuracy, units of analysis, and the environmental backcloth. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in geographic criminology. Springer, New York, pp 179–198

Kirk DS, Papachristos AV (2011) Cultural mechanisms and the persistence of neighborhood violence. Am J Soc 116:1190–1233
Kuhn TS (1962) The structure of scientific revolutions. The University of Chicago Press, Chicago
Laub JH (2004) The life course of criminology in the United States: the American Society of Criminology 2003 Presidential Address. Criminology 42:1–26
Lorenz MO (1905) Methods of measuring the concentration of wealth. Publ Am Stat Assoc 9:209–219
Mears D, Bhati D (2006) No community is an island: the effects of resource deprivation on urban violence in spatially and socially proximate communities. Criminology 44:509–548
Merton RK (1938) Social structure and anomie. Am Soc Rev 3:672–682
Miethe TD, Meier RF (1994) Crime and its social context: toward an integrated theory of offenders, victims, and situations. State University of New York Press, Albany
Morenoff JD, Sampson RJ, Raudenbush SW (2001) Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. Criminology 39:517–559
Oberwittler D, Wikstrom P (2009) Why small is better: Advancing the study of the role of behavioral contexts in crime causation. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in geographic criminology. Springer, New York, pp 35–59
Park R (1915) Suggestions for the investigations of human behavior in the urban environment. Am J Soc 20:577–612
Peterson RD, Krivo LJ (2010) divergent social worlds: neighborhood crime and the racial-spatial divide. Russell Sage Foundation, New York
Pierce GL, Spaar S, Briggs LR (1988) The character of police work: strategic and tactical implications. Northeastern University Center for Applied Social Research, Boston
Rabe-Hesketh S, Skrondal A (2012) Multilevel and longitudinal modeling using stata volume I: continuous responses, 3rd edn. Stata Press, College Station
Raudenbush SW, Bryk AS (2002) Hierarhical linear models: applications and data analysis methods, 2nd edn. Sage Publications, Thousand Oaks
Rengert G, Chakravorty S, Bole T, Henderson K (2000) A geographic analysis of illegal drug markets. Crim Prev Stud 11:219–240
Rice KJ, Smith WRC (2002) Socioecological models of automotive theft: integrating routine activity and social disorganization approaches. J Res Crime Delinq 39:304–336
Robinson W (1950) Ecological correlations and the behavior of individuals. Am Soc Rev 15:351–357
Sampson RJ (2011) The community. In: Wilson JQ, Petersilia J (eds) Crime and public policy. Oxford University Press, New York, pp 210–236
Sampson RJ (2012) Great American city: chicago and the enduring neighborhood effect. The University of Chicago Press, Chicago
Sampson RJ (2013) The place of context: a theory and strategy for criminology's hard problems. Criminology 51:1–31
Sampson RJ, Groves WB (1989) Community structure and crime: testing social-disorganization theory. Am J Soc 94:774–802
Sampson R, Raudenbush S (1999) Systematic social observation of public spaces: a new look at disorder in urban neighborhoods. Am J Soc 105:603–651
Sampson RJ, Wilson WJ (1995) Toward a theory of race, crime, and urban inequality. In: Hagan J, Peterson RD (eds) Crime and inequality. Stanford University Press, Stanford, pp 37–56
Sampson R, Raudenbush S, Earls F (1997) Neighborhoods and violent crime: a multi-level study of collective efficacy. Science 277:918–924
Sampson RJ, Morenoff JD, Earls F (1999) Beyond social capital: spatial dynamics of collective efficacy for children. Am Soc Rev 64:633–666
Sampson RJ, Morenoff JD, Gannon-Rowley T (2002) Assessing "neighborhood effects" social processes and new directions in research. Annu Rev Soc 28:443–478
Schneider VW, Wiersema B (1990) Limits and use of uniform crime reports. In: MacKenzie PJ, Roberg RR (eds) Measuring crime. State University of New York Press, Albany, pp 21–48
Shaw C, McKay H (1942) Juvenile delinquency and urban areas. The University of Chicago Press, Chicago
Shaw CR, Zorbaugh FM, McKay HD, Cottrell LS (1929) Delinquency Areas: a study of the geographic distribution of school truants, juvenile delinquents, and adult offenders in Chicago. The University of Chicago Press, Chicago
Sherman LW, Gartin PR, Buerger ME (1989) Hot spots of predatory crime: routine activities and the criminology of place. Criminology 27:27–56
Simcha-Fagan O, Schwartz JE (1986) Neighborhood and delinquency: an assessment of contextual effects. Criminology 24:667–699

Slocum TA, McMaster RB, Kessler FC, Howard HH (2005) Thematic cartography and geographic visualization. Prentice Hall, Upper Saddle River

Spelman W (1995) Criminal careers of public places. In: Eck J, Weisburd D (eds) Crime and place: crime prevention studies, vol 4. Criminal Justice Press, Monsey, pp 115–144

St. Jean PKB (2007) Pockets of crime: broken windows, collective efficacy, and the criminal point of view. The University of Chicago Press, Chicago

Steenbeek W, Weisburd D (2015) Where the action is in crime? An examination of variability of crime across spatial units in The Hague, 2001–2009. J Quant Criminol. doi:10.1007/s10940-015-9276-3

Suttles GD (1972) The social construction of communities. The University of Chicago Press, Chicago

Taylor RB (1997) Social order and disorder of street blocks and neighborhoods: ecology, microecology and the systemic model of social disorganization. J Res Crime Delinq 34:113–155

Taylor RB (2015) Community criminology: fundamentals of spatial and temporal scaling, ecological indicators, and selectivity bias. New York University Press, New York

Weisburd D (2015) The law of crime concentration and the criminology of place. Criminology 53:133–157

Weisburd D, Amram S (2014) The law of concentration of crime at place: the case of Tel Aviv-Jaffa. Police Pract Res Int J 15:101–114

Weisburd D, Bushway S, Lum C, Yang S (2004) Trajectories of crime at places: a longitudinal study of street segments in the city of Seattle. Criminology 42:283–322

Weisburd D, Bernasco W, Bruinsma G (2009) Putting crime in its place: units of analysis in geographic criminology. Springer, New York

Weisburd D, Groff ER, Yang S (2012) The criminology of place: street segments and our understanding of the crime problem. Oxford University Press, New York

Weisburd D, Telep C, Lawton B (2014) Could innovations in policing have contributed to the New York City crime drop even in a period of declining police strength?: The case of stop, question and frisk as a hot spots policing strategy. Justice Q 31:129–153

Wheeler AP, Worden RE, McLean SJ (2015) Replicating group-based trajectory models of crime at micro-places in Albany, NY. J Quant Criminol. doi:10.1007/s10940-015-9268-3

Wilcox P, Land KC (2015) Social disorganization and criminal opportunity. In: Cullen F, Wilcox P, Sampson R, Dooley B (eds) Challenging criminological theory: the legacy of Ruth Kornhauser. Transaction, New Brunswick, pp 237–258

Wirth L, Bernert EH (1949) Local community fact book of Chicago. The University of Chicago Press, Chicago

Wolfgang ME, Ferracuti F (1967) Subculture of violence: towards an integrated theory in criminology. Sage Publications, Thousand Oaks

Zorbaugh HW (1929) The gold coast and the slum: a sociological study of chicago's near north side. University of Chicago Press, Chicago